Sartorius: Detect Single Neuronal Cells in Microscopy Images

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1. Abstract

In this project *Sartorius*, we would like to implement the cell segmentation techniques using deep learning for neurological cells. Image segmentation has been tedious and mostly error prone tasks. The results on the medical field has very high cost because a single wrong result could lead to death. The research paper explores different state-of-art algorithms that are suitable for instance segmentation and object detection for medical cells. Thus, the deep learning assisted automatic segmentation techniques which that capable to catch complex pattern cells effectively than human eye, would be very beneficial for the health professionals to identify the disease cell. We believe the results form our research work will be able to contribute towards the research community.

2. Introuduction

Diseases such as Alzheimer's and brain tumors are the leading causes of death and disability each year. Currently, doctors use the lights on the cells to observe and guess the pattern and segment them and these guesses are error-prone. Thus, lack of proper segmentation tool for these neuron cells are the setbacks for an effective diagnosis and new drug discovery. Machine learning areas, especially deep learning has been used for years to solve the hard optimization problems by approximating them in different fields. Deep learning is becoming the ubiquitous method for every fields to leap forward for new innovations. More precisely talking, U-net [1] that uses the annotations technique to work with small number of available images to segment the bio-medical images. The image segmentation helps doctor to accurately find-out disease cells so that it can be detected and cured at early stage. It additionally allows the physicians to observe the cell structures and invent more effective drug for the disease.

In *Sartorius*, we would like to explore the segment and detect the *SH-SY5Y* neuroblastoma cell that has shown poor performance in segmentation method. This is an open code competition posted in Kaggle [2] which has duration of 2 more months until the project deadline. We would like to explore different techniques and implement an effective model which will provide the good result in the test dataset. The Unet model can predict the bounding boxes and IOU with more than 90% accuracy in the validation dataset for all the cell types. Additionally, we found the sample example output of the segmentation from detectron which not only segments the cell but also can provide the correct output label with high confidence. The average confidence to detect the SH-SY5Y cell is 80%. We will release the source code and openly available dataset for the research community. The dataset and implementation is available at: https://github.com/hregmi77/Sartorius

3. Approach

In this project, we would like to implement different deep learning models and compare the performance of segmentation. In *Sartorius*, We will explore following deep neural network architectures.

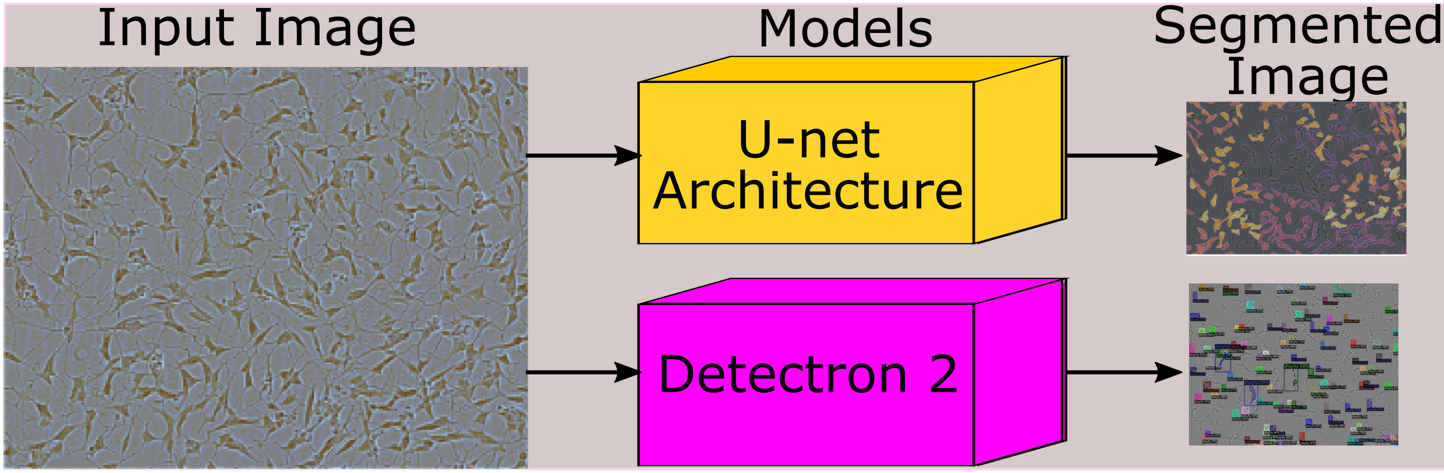


Figure 1: *Sartorius's system design for cell segmentation.*

▶ **U-net**: U-net has structure of U, and has multiple convolution (up and down) and pooling layers. It also has the skip connection, which connects the output down convolution layers directly to input of up convolution layer that has similar spatial dimension. The skip connection allows to preserve the high frequency details of the image which are lost during the encoding stage. The Unet model first removes the redundant information through encoding layers and finally reconstruct the images with the similar shape and with number of classes of different objects to generate label for different objects.

▶ **Detectron 2**: Detectron2's model zoo is the state of art library developed by facebook research community which can efficiently detect the object as well as can segment them. The training is very faster as compared to other methods and it can deployed over various different platforms. In *Sartorius*, we would like to explore this model to not only segment the rare SH-SY5Y cell but also detect its class along with confidence probability. The object class or label also includes other types of cell present in the dataset *i.e.* Astrocyte and Neuron (Corto).

▶ **Input and Output Data**: In this project, our input data is the image and output data is the segmented image that can be obtained with original image and mask. The dataset has $\sim$ 600 train images but has the large number of annotations, thus making it effectively $\sim$ 75000 images available for training.

▶ **Loss Functions**: Loss function is the core of the network and determines the objective function that we are trying to achieve. Hence, design of loss function is non-trivial. In *Sartorius*, to train the network, we will be using the categorical cross entropy loss [4] $\mathbf{L}_C = -\sum_{i=1}^{N} t_i log(c(s_i))$, where $c(s_i)$ and t_i are the predicted and actual probabilities of i^{th} class; because we are detecting the class label. Additionally, we would explore other custom losses We will include other category of losses along with cross entropy loss to improve the network.

▶ **Evaluation Metrics**: To evaluate the segmentation results, we are using *Intersection over Union* (IoU) and Dice Similarity Coefficient (DSC) along with sample-wise outputs. IoU calculates the intersection of ground truth region of cell in the image against the predicted region of the cell in the region, given by Equation 1, where A is the ground truth bounding box while B is the predicted bounding box. In *Sartorius*, we would report the *IoU* score of each test sets and visualize the performance with graph and plots.

$$IoU = \frac{A \cap B}{A \cup B} \tag{1}$$

4. Implementation

The implementation details includes the data preparation, networks design, networks training and testing, and hyper-parameters search. We also faced multiple challenges during implementation and the description on the Kaggle post are very helpful and provided the correct direction for our research.

4.1. Data Preparation

The dataset that are provided in the competition has the few images and large number of annotations, thus we have to write an algorithm to generate the multiple samples from the training images. There are only 600 actual images present in the training set. From them, we are generating the ~ 75000 data samples that are available for training. Additionally, the masks are provided in running length sequence, which needed to be decoded before using decoding algorithm that are available open-source to generate the actual mask to compute the IoU and DSC coefficients.

4.2. Network Selections

We are selecting the Unet model that is the baseline model for our segmentation task. In the Unet model, we are loading the EfficientNet0 model architecture and pretrained weights from the ImageNet to start model training. Loading of pretrained model weights allows us to direct the training process in right direction as well as the network can learn from thousands of different image features that were trained prior in ImageNet model.

However, Unet model only gives the mask and not the object class thus, we would like to explore a model that can not only provide the correct mask but also detects the cell type. We use the facebook's detectron 2 model zoo for detection and segmentation purposes. The model zoo have been used in multiple state-of-art techniques to detect numerous objects. Hence, it is best model for our problem to detect the cell as well as segment it with high accuracy.

4.3. Network Training

Both networks are trained and tested on the same training and validation dataset. The Unet model is implemented using Tensorflow API for deep learning training and Python language. It takes $\sim$ 5-6 hrs to train for 15 epochs with GeForce GTX 1070 Nvidia GPU. Similarly, we trained the Detectron2 model in the similar settings and it took a similar amount of time to train. The Detectron2 model is implemented in PyTorch deep learning API and Python.

5. Evaluation

Evaluation Summary: We are training and testing two different models *i.e.* Unet and Detectron2 model zoo. In Unet model, we are exploring in details about how much accurately we can segment the corresponding cell without considering the cell type and the results shows we can achieve more than 90% IoU and DSC socre. Additionally, in Detectron2 model, we are able to predict the correct cell types with more than ~ 80 % confidence probability for rare SH-SY5Y cells.

5.1. Unet

The Unet model is trained and validated with larger annotation examples. As seen in figure 2(a), the network's validation loss reduces gradually and flats out and follows the training loss. The network loss quickly drops significantly within few epochs which indicates the Unet segmentation model is fast trainable. Also, the validation and traiing losses are following the trend in the successive epochs. This indicates that the model is training without any overfitting. Similarly, figure 2(b) shows the networks performance for segmentation, where we observe that it can achieve the Intersection of Union (IoU) and

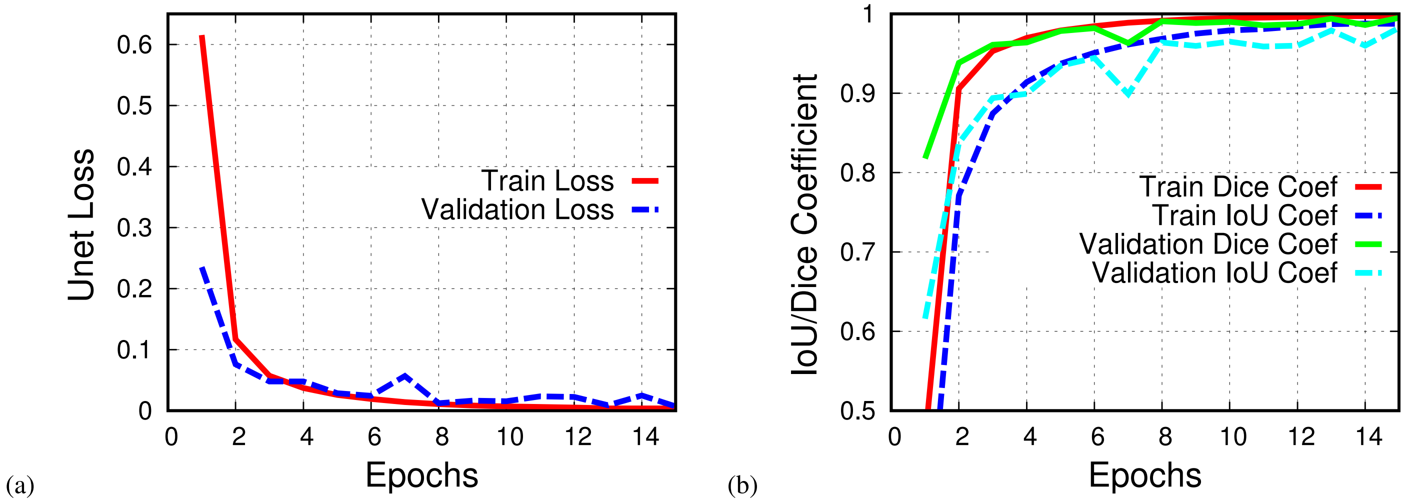


Figure 2: *Sartorius's Unet ; (a)Training and validation loss w.r.t. epochs (b) Train and validation IoU and Dice w.r.t. epochs*

Dice Similarity Coefficient (DSC) of more than 90% after 4-5 epochs and achieve upto 98 % on validation data with more training.

5.2. Detectron 2

The detectron2 is the successor of mask-rcnn benchmark and detectron models. The detectron2 model zoo performs the instance segmentation as well as object detection with higher confidence. As seen in figure 3 is the sample output from the test cases where we detect multiple SH-SY5Y cells in the image with various confidences. We achieve the probability confidences ranging from 54% to 90%. The difference instances of SH-SY5Y cells are plotted with different colors indicating multiple cells in a single image. Additionally, we observe in figure 4(a–b) the outputs of other cells with high accuracy and confidence in other cell types. In the provided dataset, we have multiple instances of 3 types of cell. Figure 4(a) shows the instance segmentation and cell detection of cort neuron cells with 50%-99% and figure 4(b) shows the output of Astrocytes cell for instance segmentation and cell detection and we observe that it can achieve the confidence upto 98% on few cell segments.

6. Conclusion

In *Sartorius* project, we are able to successfully perform the baseline segmentation using Unet with higher accuracy. In addition to that we are also able to detect the particular cell type with detectron2 model. This allows medical professionals to not only find the region of the cell but also know about the types of cell present in the image.

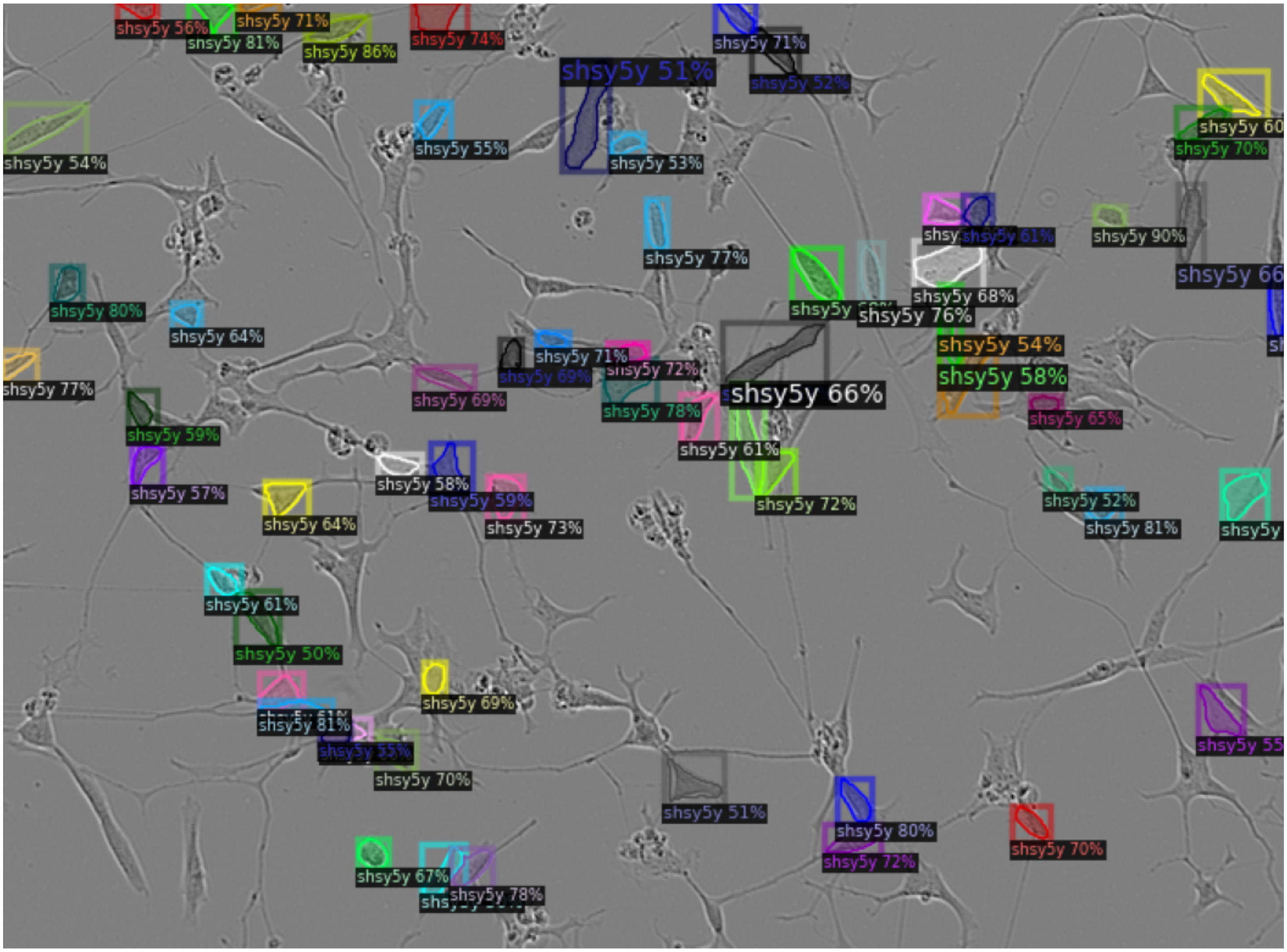


Figure 3: *Sartorius's Detectron2 Model output mask with confidence for SH-SY5Y cells.*

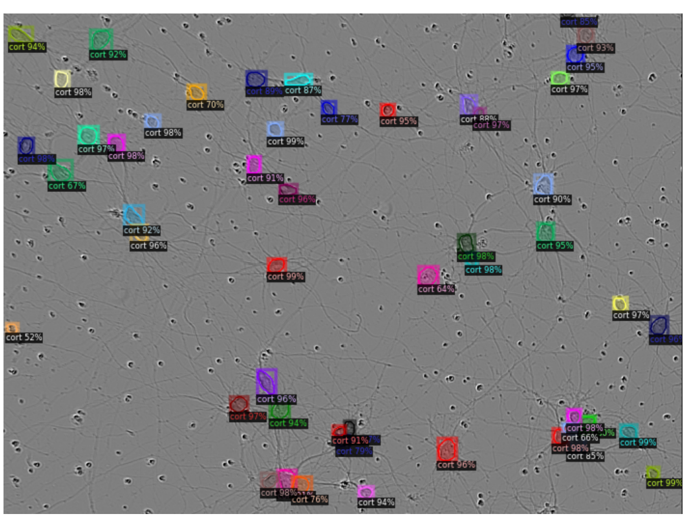
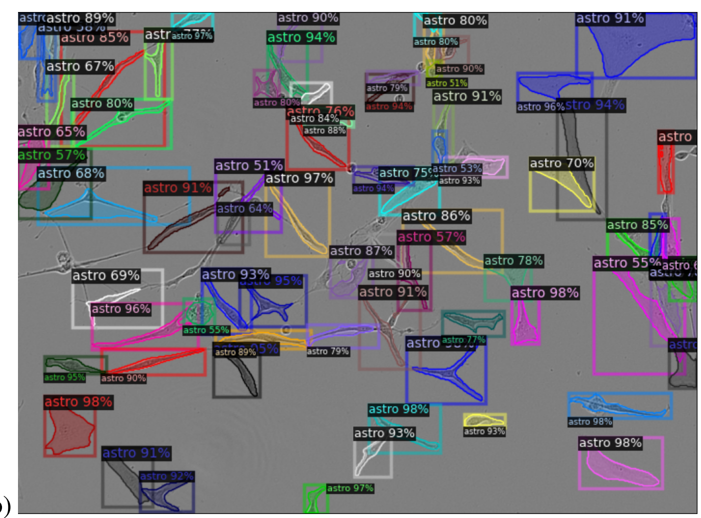
(a) 
(b) 

Figure 4: *Sartorius's Detectron2 Model output mask with confidence for ; (a) Cort (Neuron) cells (b) Astrocytes cells*

References

[1] Olaf Ronneberger and Philipp Fischer and Thomas Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," 2015.

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[4] Raul Gomez Blog, "Understanding Categorical Cross-Entropy Loss, Binary Cross-Entropy Loss," 2021. [Online]. Available: https://gombru.github.io/2018/05/23/cross_entropy_loss/